Robust switching vector median filter for impulsive noise removal

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Abstract. *We present an order-statistics-based vector filter for the removal of impulsive noise from color images. The filter preserves the edges and fine image details by switching between the identity (no filtering) operation and the vector median filter operation based on the robust univariate median operator. Experiments on a diverse set of images and comparisons with state of the art filters shows that the proposed filter combines simplicity, flexibility, excellent filtering quality, and low computational requirements.* © *2008 SPIE and IS&T.* [DOI: 10.1117/1.2991415]

1 Introduction

The growing use of color images in diverse applications such as content-based image retrieval, medical image analysis, remote sensing, and visual quality inspection has led to an increased interest in color image processing. These images are often contaminated with noise, which is often introduced during acquisition or transmission. In particular, the introduction of bit errors and impulsive noise into an image not only lowers its perceptual quality, but also makes subsequent tasks such as edge detection and segmentation more difficult. Therefore, the removal of such noise is often a necessary preprocessing step in color image processing applications.

Numerous filters have been proposed for the removal of impulsive noise from color images.[1,2] Among these, nonlinear vector filters have proved successful in the preservation of edges and fine details while removing the noise.[1] Early approaches to nonlinear filtering of color images often involved the application of a scalar filter to each color channel independently. However, since separate processing ignores the inherent correlation between the color channels, these methods often introduce color artifacts to which the human visual system is very sensitive. Therefore, vector filtering techniques that treat the color image as a vector field and process color pixels as vectors are more appropriate. An important class of nonlinear vector filters is the one based on robust order statistics, with the vector median filter (VMF),[3] the basic vector directional filter (BVDF),[4] and the directional-distance filter (DDF)[5] being the most widely known examples. These filters involve reduced ordering[6] of a set of input vectors within a window to determine the output vector.

The fundamental order-statistics-based filters (VMF, BVDF, and DDF), as well as their fuzzy[7] and hybrid[8] extensions, share a common deficiency in that they are implemented uniformly across the image and tend to modify pixels that are not corrupted by noise. This results in excessive smoothing and the consequent blur of edges and loss of fine image details. To overcome this, intelligent filters that switch between the identity operation and a robust order-statistics-based filter such as the VMF have been introduced.[9–15] These filters determine whether the pixel under consideration is noisy or not in the context of its neighborhood. In the former case, the pixel is replaced by the output of the noise removal filter; otherwise, it is left unchanged to preserve the desired (noise-free) signal structures. Such an approach is often computationally efficient considering that the expensive filtering operation is performed only on the noisy pixels, which usually comprise a small percentage of the image.

In this work, we introduce a new switching filter for the removal of impulsive noise from color images. The filter utilizes the robust median statistic to determine whether or not the center pixel of a neighborhood is noisy. If the center pixel is noisy, it is replaced by the VMF output, i.e., the pixel that minimizes the sum of distances to all other pixels in the neighborhood. Otherwise, it is left unchanged. The method is tested on a diverse set of images. The results demonstrate that the proposed filter is not only fast, but also gives excellent results in comparison to various state of the art filters.

The rest of the work is organized as follows. Section 2 describes the proposed method. Section 3 describes the noise model, filtering performance criteria, and the experimental setup. Finally, Sec. 4 gives the conclusions.

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$$\begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \mathbf{x}_3 \\ \mathbf{x}_4 & \mathbf{x}_5 & \mathbf{x}_6 \\ \mathbf{x}_7 & \mathbf{x}_8 & \mathbf{x}_9 \end{bmatrix}$$

Fig. 1 Indexing convention for color vectors inside a 3×3 window.

2 Proposed Method

Consider an $M\times N$ RGB image $\mathbf{X}$ that represents a 2-D array of three-component vectors $\mathbf{x}(r,c)=[x_1(r,c),x_2(r,c),x_3(r,c)]$ occupying the spatial location (r,c), with the row and column indices $r=1,2,\ldots,M$ and $c=1,2,\ldots,N$, respectively. In the color pixel $\mathbf{x}(r,c)$, the $x_k(r,c)$ values denote the red $(k=1)$, green $(k=2)$, and blue $(k=3)$ components. To isolate small image regions, each of which can be treated as stationary, a supporting window $W(r,c)$ centered on pixel $\mathbf{x}(r,c)$ is used. The window slides over the entire image $\mathbf{X}$ and the procedure replaces the vector $\mathbf{x}(r,c)$ with the output $\mathbf{y}(r,c)=F[W(r,c)]$ of a filter function $F(.)$ that operates over the samples within $W(r,c)$. Repeating the procedure for $r=1,2,\ldots,M$ and $c=1,2,\ldots,N$ produces the pixels $\mathbf{y}(r,c)$ of the filtered image $\mathbf{Y}$. For notational simplicity, the vectors inside $W(r,c)$ are reindexed as $W(r,c)=\{\mathbf{x}_i:i=1,2,\ldots,n\}$ (see Fig. 1), as commonly seen in the related literature.[1,2] In this notation, the center pixel in W is given by $\mathbf{x}_{(n+1)/2}$.

Order-statistics-based vector filters operate by ranking the vectors inside the filter window using various criteria. For example, the VMF uses the cumulative Minkowski distance criterion and determines the lowest-ranked input vector as the output vector $\mathbf{x}_{\mathrm{VMF}}$:

$$\mathbf{y}(r,c)=\mathbf{x}_{\mathrm{VMF}}=\underset{\mathbf{x}_i\in W(r,c)}{\operatorname{argmin}}\sum_{j=1}^{n}\|\mathbf{x}_i-\mathbf{x}_j\|_p, \qquad (1)$$

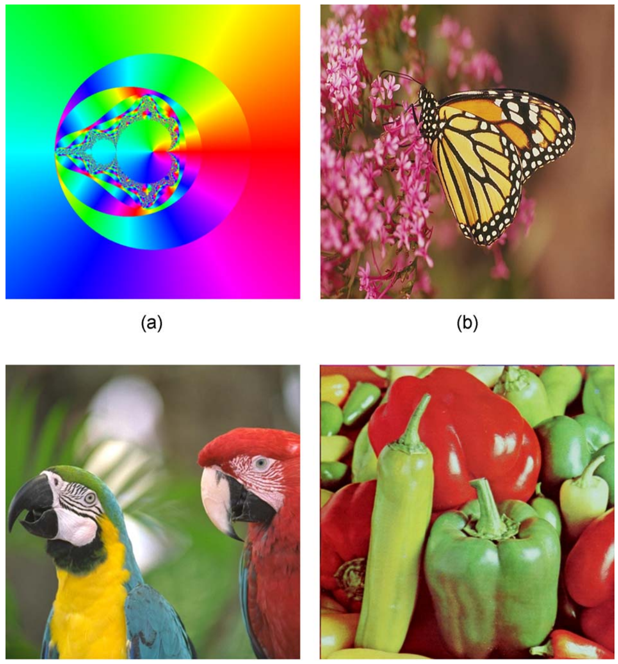
where $\|.\|_p$ denotes the L_p (Minkowski) norm.

As mentioned earlier, VMF-like nonswitching filters tend to modify pixels that are not corrupted by noise, which results in excessive smoothing and thus the blurring of edges and loss of fine image details. To address this problem, we propose a new filter called the robust switching vector median filter (RSVMF). The proposed filter determines the output vector in a window according to the following rule:

$$d_i=\sum_{j=1}^{n}\|\mathbf{x}_i-\mathbf{x}_j\|_p \qquad (2)$$

$$\mathbf{y}(r,c)=\mathbf{x}_{\mathrm{RSVMF}}=\begin{cases}\mathbf{x}_{(n+1)/2} & \text{if } d_{(n+1)/2}\leqslant\alpha\cdot\operatorname{med}(d_1,d_2,\ldots,d_n),\\ \mathbf{x}_{\mathrm{VMF}} & \text{otherwise}\end{cases}$$

where d_i is the cumulative distance associated with pixel x_i, α is a tuning parameter, and med (.) is the robust univariate median operator.



(a) (b) (c) (d)

Fig. 2 Representative images from the test set: (a) Mandelbrot-hue, (b) Monarch, (c) Parrots, and (d) Peppers.

The RSVMF operates as follows. First, it determines whether or not the center pixel is noisy. A noisy pixel is one whose cumulative Minkowski distance is greater than the median cumulative distance in its neighborhood. If the center pixel is noisy, it is replaced by the VMF output. Otherwise, it remains unchanged. The switching threshold can be adjusted using the α parameter.

The rationale behind the choice of the median operator is its statistically robust nature. In other words, this operator is resistant to noise, which makes it a suitable threshold operator. The proposed filter utilizes this robust operator to determine whether the cumulative distance associated with the center pixel is significantly greater than a "typical" cumulative distance in the neighborhood. If this is the case, the center pixel is considered to be noisy and is replaced by the VMF output. Otherwise, it is left unchanged to preserve the image details.

3 Experimental Results

In this section, we evaluate the performance of the RSVMF on a set of test images commonly used in the color image filtering literature. Figure 2 shows representative images from this set. In the experiments, the filtering window is set to 3×3 and the L_2 norm is used whenever the Minkowski distance is involved.

3.1 *Noise Model and Error Metrics*

Several simplified color image noise models have been proposed in the literature.[1] In this study, the widely used impulsive noise model[16] is adopted:

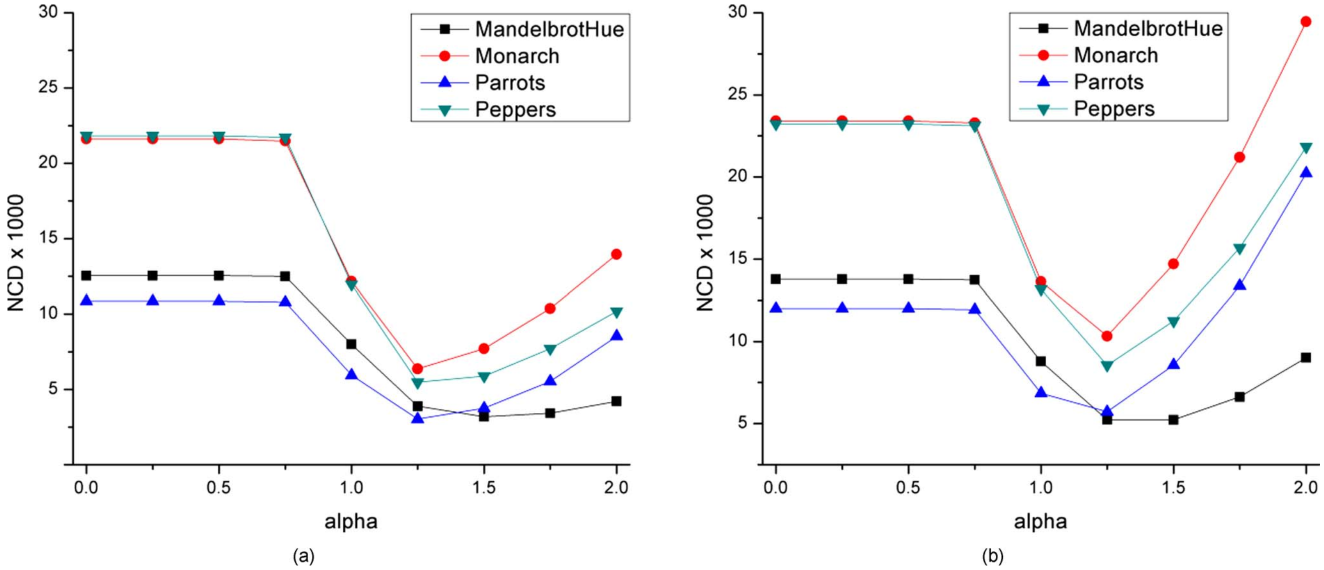


Fig. 3 α versus NCD at noise levels (a) 10% and (b) 15%.

$$\mathbf{x} = \begin{cases} \mathbf{o} & \text{with probability } 1-\varphi \\ \{r_1,o_2,o_3\} & \text{with probability } \varphi_1 \cdot \varphi \\ \{o_1,r_2,o_3\} & \text{with probability } \varphi_2 \cdot \varphi \\ \{o_1,o_2,r_3\} & \text{with probability } \varphi_3 \cdot \varphi \\ \{r_1,r_2,r_3\} & \text{with probability } [1-(\varphi_1+\varphi_2+\varphi_3)] \cdot \varphi \end{cases}, \tag{3}$$

where $\mathbf{o}=\{o_1,o_2,o_3\}$ and $\mathbf{x}=\{x_1,x_2,x_3\}$ represent the original and noisy color vectors, respectively, $\mathbf{r}=\{r_1,r_2,r_3\}$ is a random vector that represents the impulsive noise, φ is the sample corruption probability, and φ_1, φ_2, and φ_3 are the corruption probabilities for the red, green; and blue channels, respectively. In the simulations, the channel corruption probabilities were set to 0.25.

To evaluate the performance of the proposed filter, the following error metrics are used: mean absolute error (MAE),[1] mean squared error (MSE),[1] and normalized color distance (NCD).[1] MAE and MSE are based on the RGB color difference and measure the detail preservation and noise suppression capability of a filter, respectively. NCD is

Table 1 Comparison of the noise detection performance at 10% noise level.

	Mandelbrot-hue		Monarch		Parrots		Peppers	
Filter	SE%	SP%	SE%	SP%	SE%	SP%	SE%	SP%
ABVDF	68.58	97.58	94.93	99.58	92.81	99.98	86.36	99.61
ASBVDF	67.88	99.28	92.31	93.00	93.32	95.91	85.98	91.78
ASDDF	68.52	99.30	92.01	94.46	92.10	96.77	87.31	93.49
ASVMF	68.85	99.35	89.23	94.02	89.54	95.94	87.54	93.32
AVMF	62.91	99.11	71.20	99.89	70.54	99.99	69.38	99.99
EBVDF	67.29	98.35	91.57	92.35	91.31	94.96	85.42	89.70
EDDF	68.69	99.20	93.96	92.85	93.67	95.54	89.35	91.58
EVMF	69.48	99.31	90.62	93.45	90.62	95.38	88.82	92.65
FPGF	70.52	96.09	93.89	97.79	92.68	99.23	90.20	98.87
RSYMF	**72.24**	**99.73**	**97.09**	**95.84**	**97.69**	**96.49**	**95.23**	**96.17**
VSDROMF	71.85	95.78	97.54	96.69	96.33	98.79	93.91	98.31

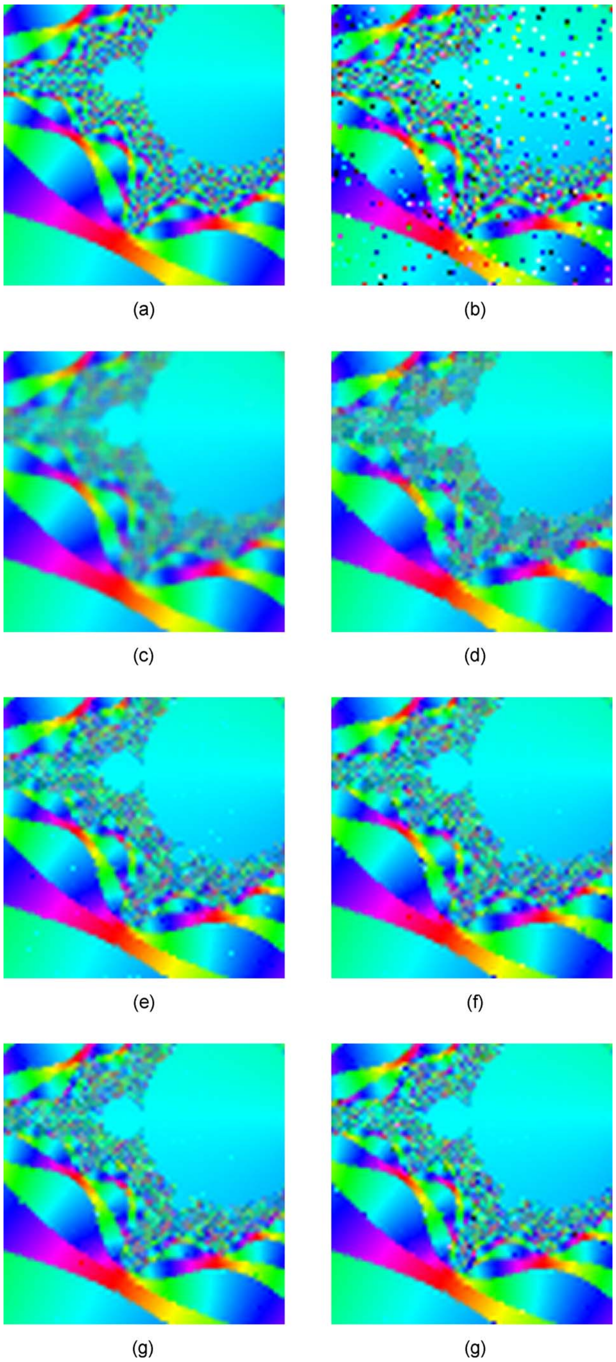


Fig. 4 Filtering results for the Mandelbrot-hue image corrupted with 10% noise: (a) original, (b) 10% noisy (MAE 6.35, MSE 1427.90), (c) AMNFE (MAE 1.66, MSE 88.71), (d) VMF (MAE 1.43, MSE 109.29), (e) AVMF (MAE 0.95, MSE 86.90), (f) ASVMF (MAE 0.77, MSE 78.77), (g)EVMF (MAE 0.75, MSE 72.66), (h) RSVMF (MAE 0.41, MSE 45.89).

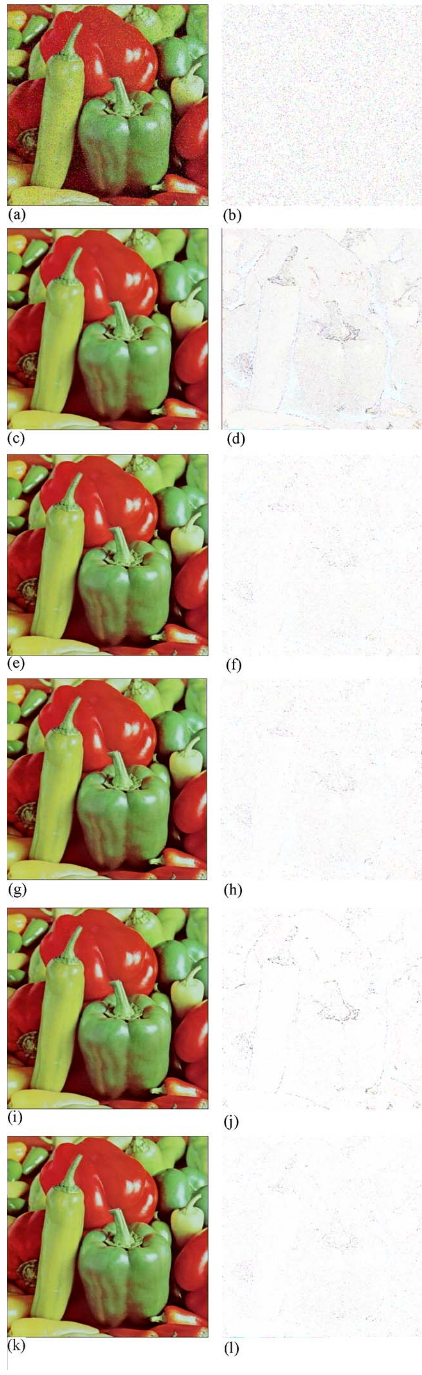


Fig. 5 Filtering results for the Peppers image corrupted with 10% noise: (a) 10% noisy, (b) MAE 6.34, MSE 1035.05, (c) VMF, (d) MAE 2.29, MSE 20.38, (e) ASVMF, (f) MAE 0.79, MSE 21.67, (g) EVMF, (h) MAE 0.77, MSE 20.12, (i) VSDROMF, (j) MAE 0.58, MSE 11.67, (k) RSVMF, and (l) MAE 0.55, MSE 10.59.

a perceptually oriented metric based on the CIELAB color difference formula that measures the color preservation capability of a filter.

3.2 *Parameter Selection*

There is only a single parameter involved in the proposed filter, α. Higher values of α preserve the image details better, whereas lower values remove the noise better, i.e., produce smoother results. As α approaches 0, the RSVMF turns into the VMF, i.e., maximum filtering is performed. On the other hand, as α approaches ∞, the RSVMF turns into the identity filter, i.e., no filtering is performed. Figure 3 shows the NCD values obtained using various α values at 10 and 15% noise levels.

It can be seen that $\alpha = 1.25$ achieves the best filtering

Table 2 Comparison of the filters at 10% noise level.

Filter	MAE	MSE	NSD	Time	MAE	MSE	NCD	Time
	Mandelbrot-hue (512×515 pixels)				Monarch (512×515 pixels)			
None	6.347	1427.902	60.894	0.000	6.353	979.097	122.597	0.000
ABVDF	1.276	111.850	11.304	8.317	0.607	22.212	6.637	14.936
AMNFE	1.662	88.709	14.077	0.553	2.307	25.542	25.531	0.839
ASBVDF	0.847	95.326	7.862	7.964	0.966	53.186	11.521	14.347
ASDDF	0.793	83.429	7.340	8.103	0.683	23.768	9.226	14.548
ASVMF	0.774	78.773	7.084	0.351	0.762	28.382	11.089	0.556
AVMF	0.952	86.901	8.710	0.442	0.951	54.617	19.910	0.702
BVDF	1.499	119.063	13.240	7.918	2.692	53.821	25.270	14.250
DDF	1.443	110.004	12.791	8.177	2.121	32.603	21.259	14.655
EBVDF	0.920	110.200	8.624	3.522	1.140	78.742	14.065	6.873
EDDF	0.802	83.284	7.453	3.538	0.749	27.142	9.300	6.942
EVMF	0.746	72.663	6.801	0.522	0.743	25.839	10.503	0.847
FPGF	1.331	106.246	11.650	0.091	0.675	20.631	7.446	0.147
FVMF	1.448	94.995	12.712	2.771	2.226	26.811	22.739	4.624
FVMRHF	0.815	58.945	7.245	1.922	1.332	14.851	15.070	2.903
KVMF	1.360	106.967	11.911	0.430	1.089	23.176	10.776	0.680
MMF	1.395	101.338	12.887	0.043	2.045	29.484	27.042	0.089
RSVMF	**0.414**	**45.888**	**3.867**	**0.383**	**0.537**	**15.947**	**6.364**	**0.614**
VMF	1.430	109.288	12.624	0.337	2.103	31.565	21.558	0.511
VMRHF	0.792	60.933	7.004	0.444	1.048	15.416	10.642	0.689
VSDROMF	1.374	109.149	12.012	0.428	0.844	24.878	7.664	0.691
	Parrots (768×512 pixels)				Peppers (512×512 pixels)			
None	6.359	1002.586	117.103	0.000	6.343	1035.054	95.664	0.000
ABVDF	0.504	38.254	4.816	14.216	0.717	40.445	8.952	10.283
AMNFE	1.400	9.197	14.716	0.836	2.458	19.088	24.109	0.547
ASBVDF	0.687	47.965	7.488	13.669	1.090	59.822	12.793	9.900
ASDDF	0.466	21.001	5.904	13.876	0.860	35.470	10.186	10.041
ASVMF	0.503	16.714	7.370	0.549	0.786	21.671	9.140	0.369
AVMF	0.773	45.208	16.543	0.699	0.859	45.153	13.685	0.469
BVDF	1.708	23.265	13.617	13.575	2.828	46.261	26.490	9.841
DDF	1.231	10.927	10.469	13.967	2.289	19.117	21.729	10.100
EBVDF	0.827	72.025	9.707	6.653	1.367	112.720	16.216	4.808

Table 2 (*Continued.*)

Filter	MAE	MSE	NSD	Time	MAE	MSE	NCD	Time
EDDF	0.473	19.832	5.602	6.430	0.850	28.923	9.572	4.769
EVMF	0.494	15.658	6.975	0.828	0.774	20.124	8.725	0.565
FPGF	0.339	7.128	4.255	0.139	0.520	11.357	5.677	0.094
FVMF	1.329	9.043	12.275	4.528	2.353	17.173	22.143	3.135
FVMRHF	0.843	5.608	8.369	2.888	1.523	11.456	15.140	1.936
KVMF	0.548	6.506	5.437	0.676	1.002	11.667	9.309	0.455
MMF	1.205	9.749	14.129	0.080	2.204	19.842	24.460	0.060
RSVMF	**0.309**	**6.013**	**3.119**	**0.609**	**0.547**	**10.585**	**5.486**	**0.411**
VMF	1.236	10.625	10.864	0.509	2.286	20.380	21.828	0.344
VMRHF	0.611	5.690	5.223	0.684	1.164	11.732	10.790	0.461
VSDROMF	0.378	7.105	3.415	0.680	0.576	11.665	5.391	0.458

results. Similar trends were observed on other test images. Note that on some highly textured images, $\alpha=1.5$ may achieve better results.

3.3 *Comparison with State of the Art Filters*

In this section, we compare the proposed filter with several nonswitching and switching impulsive noise removal filters. The nonswitching filters include the marginal (component-wise) median filter (MMF), VMF, BVDF, DDF, AMNFE,[17] FVMF,[7] VMRHF[18] FVMRHF,[8] and KVMF.[19] The switching filters include the VSDROMF,[9] ABVDF,[10] AVMF,[11] EVMF,[12] EBVDF,[12] EDDF,[12] FPGF,[13] ASVMF, ASBVDF, and ASDDF.[14]

Figure 4 shows the filtering results for a close-up of the Mandelbrot-hue image. Figures 4(c) and 4(d) show the outputs of the nonswitching filters, i.e., the AMNFE and VMF. It can be seen that even though these filters suppress the noise very well, this comes at the expense of the blurring of image details. On the other hand, the switching filters, i.e., the AVMF, ASVMF, EVMF, and RSVMF, preserve the details much better. Among these, the RSVMF strikes the best balance between noise removal and detail preservation.

Figure 5 shows the filtering results for a section of the Peppers image and the corresponding difference images. To obtain the difference images, the pixel-wise absolute differences between the original and the corresponding filtered images were multiplied by five and then negated. As expected, the VMF output shows significant differences when compared to the original image. In contrast, the switching filters show a clear improvement in restoring the original image. Among these, it can be seen that the RSVMF gives the best result.

Table 1 compares the switching filters in terms of their noise (impulse) detection capability. Here SE (sensitivity) and SP (specificity)[20] indicate a filter's accuracy in detecting noisy pixels and noise-free pixels, respectively. It can be seen that the RSVMF has the highest noise detection accuracy, which demonstrates the effectiveness of its switching criterion, i.e., Eq. (2).

Tables 2 and 3 compare the filters using the criteria described in Sec. 3.1, i.e., MAE, MSE, NCD (multiplied by 1000), and the execution time in seconds [The results are the average to Ten runs (programming language: C. Compiler: gcc 3.4.4. CPU: Intel Pentium D 2.66 Ghz)]. It can be seen that the RSVMF compares favorably with the best filters in terms of filtering effectiveness as assessed by the first three criteria. With respect to the execution speed, the RSVMF ranks fifth, after the VMF, ASVMF, FPGF, and MMF. This is expected, since the computational requirements of the RSVMF are the same as that of the VMF with the exception of the extra median operation, which can be performed rapidly using a minimum exchange network algorithm.

In summary, the proposed filter has the following advantages.

- Simplicity: it is intuitive and easy to implement.
- Flexibility: the parameter α can be used to fine tune the filtering behavior; lower values smooth the image more, whereas higher values preserve the image details better.
- Excellent filtering quality: it removes the noise and preserves the details and the color content of the image well, as indicated by the low MAE, MSE, and NCD values in Tables 2 and 3.
- Low computational requirements: its computational requirements are slightly higher than the VMF.

4 Conclusions

We introduce a fast switching filter for the removal of impulsive noise from color images. The proposed filter uti-

Table 3 Comparison of the filters at 15% noise level.

Filter	MAE	MSE	NCD	Time	MAE	MSE	NCD	Time
	(512×512 pixels)				Monarch (512×512 pixels)			
None	9.510	2140.743	91.506	0.000	9.532	1468.798	184.047	0.000
ABVDF	1.422	126.534	12.647	8.303	0.886	33.291	9.770	14.905
AMNFE	1.908	96.107	16.075	0.561	2.569	30.770	30.547	0.844
ASBVDF	1.117	131.610	10.636	7.953	1.442	107.128	19.235	14.327
ASDDF	1.006	107.264	9.548	8.091	1.009	47.847	15.951	14.524
ASVMF	0.955	97.194	8.967	0.358	1.099	51.681	18.858	0.550
AVMF	1.135	101.292	10.514	0.447	1.420	81.494	29.983	0.708
BVDF	1.628	132.248	14.390	7.895	2.914	62.804	27.359	14.223
DDF	1.552	118.807	13.840	8.161	2.302	37.674	23.107	14.623
EBVDF	1.276	168.259	12.216	3.767	1.758	159.907	24.456	7.111
EDDF	1.035	114.195	9.865	3.792	1.062	55.786	15.297	7.214
EVMF	0.921	91.352	8.632	0.539	1.057	48.601	17.839	0.856
FPGF	1.436	114.755	12.654	0.102	0.921	27.058	10.562	0.716
FVMF	1.532	100.540	13.503	2.834	2.363	30.311	23.943	4.625
FVMRHF	0.912	69.012	8.209	1.927	1.500	20.945	16.911	2.908
KVMF	1.462	115.410	12.876	0.437	1.345	28.821	13.498	0.684
MMF	1.483	109.229	13.759	0.045	2.178	34.221	30.044	0.091
RSVMF	**0.535**	**62.995**	**5.114**	**0.386**	**0.753**	**30.649**	**10.298**	**0.619**
VMF	1.531	117.224	13.597	0.334	2.288	36.613	23.419	0.516
VMRHF	0.887	71.444	7.951	0.450	1.234	22.051	12.853	0.7000
VSDROMF	1.476	117.375	12.965	0.431	1.069	30.278	10.125	0.691
	Parrots (768×512 pixels)				Peppers (512×512 pixels)			
None	9.534	1503.510	175.752	0.000	9.513	1553.101	143.724	0.000
ABVDF	0.767	57.076	7.441	14.245	1.089	63.277	13.608	10.161
AMNFE	1.628	12.268	19.052	0.844	2.694	23.841	27.545	0.558
ASBVDF	1.118	97.684	13.730	13.689	1.582	114.213	20.186	9.778
ASDDF	0.769	46.025	11.283	13.897	1.217	67.192	16.086	9.919
ASVMF	0.786	35.250	13.715	0.548	1.077	42.096	14.327	0.369
AVMF	1.171	68.534	24.995	0.703	1.299	68.079	20.608	0.470
BVDF	1.837	27.368	14.858	13.592	3.048	61.883	28.809	9.717
DDF	1.338	12.539	11.583	13.986	2.436	22.224	23.166	9.981
EBVDF	1.404	150.502	18.604	6.722	2.058	211.967	26.333	4.843

Table 3 (*Continued.*)

Filter	MAE	MSE	NCD	Time	MAE	MSE	NCD	Time
EDDF	0.751	46.185	10.537	6.831	1.197	63.682	15.202	4.839
EVMF	0.762	34.771	13.095	0.844	1.050	40.446	13.677	0.570
FPGF	0.498	10.304	6.369	0.170	0.752	15.975	8.417	0.111
FVMF	1.412	10.295	13.037	4.553	2.460	19.284	23.052	3.130
FVMRHF	0.943	8.405	9.432	2.902	1.661	15.985	16.551	1.939
KVMF	0.697	8.472	6.926	0.680	1.236	14.957	11.562	0.462
MMF	1.279	11.446	15.730	0.078	2.306	23.483	26.307	0.063
RSVMF	**0.458**	**15.469**	**5.622**	**0.609**	**0.747**	**22.776**	**8.382**	**0.414**
VMF	1.348	12.384	11.995	0.512	2.428	23.212	23.190	0.344
VMRHF	0.727	8.768	6.534	0.687	1.326	16.713	12.543	0.467
VSDROMF	0.513	9.163	4.843	0.680	0.790	14.992	7.659	0.459

lizes the robust univariate median operator to switch between the identity operation and the vector median filter operation. Experiments on a diverse set of images and comparisons with state of the art filters show that the proposed filter combines simplicity, flexibility, excellent filtering quality, and low computational requirements.

A common problem with the current switching vector filters is that they often perform excessive smoothing in highly textured areas. Future work will be directed toward the design of adaptive switching criteria that can distinguish between a textured and noisy neighborhood.

The implementations of the filters described in this work will be made publicly available as part of the Fourier image processing and analysis library, which can be downloaded from http://sourceforge.net/projects/fourier-ipal.

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